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# Edge-Intelligence-Based Dynamic Spectrum Allocation for 6G Wireless Networks

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**Abstract:** The rapid proliferation of ultra-dense 6G networks has intensified the challenges of real-time spectrum management, as traditional centralized or static allocation methods struggle to achieve a balance among responsiveness, energy efficiency, and scalability. Existing approaches that rely on global coordination incur considerable signaling overhead and fail to adapt effectively to non-stationary wireless environments. To address these limitations, this study introduces an Edge-Intelligence-Based Dynamic Spectrum Allocation (EI-DSA) framework that integrates deep reinforcement learning (DRL) with federated learning (FL) for localized spectrum prediction and distributed decision-making. Utilizing empirical parameters derived from the NTT Docomo Tokyo 6G Testbed and Huawei Futian CBD Field Trials, the proposed framework achieves notable improvements-8.8% higher spectrum utilization, 26% lower latency, and 43% better energy efficiency-compared with centralized RL and proportional fairness baselines. The findings validate that embedding edge intelligence within radio access networks enables real-time, energy-aware, and privacy-preserving control. Theoretically, this research bridges communication engineering and intelligent optimization, presenting a scalable paradigm for AI-native 6G systems. Practically, it provides design guidance for developing green, autonomous, and adaptive wireless infrastructures that align with next-generation communication and electronic engineering advancements.

**Keywords:** edge intelligence; 6G networks; dynamic spectrum allocation; federated reinforcement learning; energy efficiency

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## 1. Introduction

The evolution toward sixth-generation (6G) wireless communication represents a paradigm shift from throughput-oriented design to intelligence-driven connectivity [1]. In ultra-dense urban environments such as Tokyo's Shibuya Station and Shenzhen's Futian Central Business District, thousands of small cells, IoT sensors, and autonomous devices operate within confined radio spaces, creating highly dynamic and heterogeneous spectrum demands [2]. The exponential growth of connected devices-expected to exceed $10^6$ per $km^2$ by 2030-places unprecedented pressure on radio spectrum management. Under such conditions, static or centrally controlled spectrum allocation schemes are no longer sufficient to ensure the real-time responsiveness, energy efficiency, and low latency required by mission-critical applications such as autonomous driving, telemedicine, and extended reality (XR) streaming [3].

Conventional methods, including heuristic scheduling and optimization-based dynamic spectrum access, depend heavily on global coordination and static parameter tuning [4]. Although effective in 5G macro-cell environments, these methods fail to scale within 6G's heterogeneous edge infrastructure due to excessive signaling overhead and limited adaptability to rapidly changing local conditions [5]. Furthermore, cloud-centric management introduces additional latency and energy consumption, particularly when frequent channel state updates must be transmitted from edge nodes to centralized controllers [6]. While recent advances in deep learning and reinforcement learning have enabled partial automation of spectrum allocation, their dependence on centralized training and homogeneous datasets restricts adaptability in non-stationary wireless environments [7]. This limitation underscores the need for distributed, context-aware spectrum management frameworks capable of autonomous operation at the network edge.

To overcome these challenges, this study proposes an Edge-Intelligence-Based Dynamic Spectrum Allocation (EI-DSA) framework that integrates edge AI prediction models with distributed decision-making mechanisms. Each edge node utilizes local traffic observations and spectral characteristics to predict short-term demand variations through hybrid deep reinforcement learning (DRL), enhanced by federated learning (FL) for collaborative model updating. This hybrid approach reduces communication overhead and alleviates the effects of environmental non-stationarity while preserving data privacy and local autonomy. A case study based on ultra-dense 6G testbeds deployed in Tokyo and Shenzhen is conducted to validate the proposed framework under realistic mobility and interference conditions.

Methodologically, this research combines literature analysis, simulation-based performance evaluation, and comparative experiments against conventional allocation schemes such as Q-learning and proportional fairness (PF). The evaluation focuses on three key metrics-spectrum utilization, latency, and energy efficiency-which collectively capture the trade-off between communication performance and computational cost.

The significance of this study lies in both its theoretical and practical contributions. Theoretically, it advances the foundation of distributed edge intelligence for spectrum management by introducing a scalable model that learns and adapts dynamically at the network periphery. Practically, it offers a feasible solution for real-time, low-latency spectrum coordination in next-generation communication systems, providing insights for 6G infrastructure planning, energy-aware network control, and AI-native protocol design. By integrating principles of communication engineering with intelligent optimization algorithms, this research contributes to the realization of self-optimizing 6G networks that embody both efficiency and autonomy.

## 2. Literature Review

### *2.1. Dynamic Spectrum Management in Next-Generation Networks*

Dynamic spectrum management has become a fundamental component of efficient wireless communication. Traditional schemes, such as static frequency reuse and proportional fairness, performed well in 5G macro-cell systems due to their analytical simplicity and relatively stable traffic patterns [8]. However, these rule-based and centrally controlled methods are inadequate for coping with the rapidly changing interference and high device density characteristic of 6G environments [9]. Machine-learning-based dynamic spectrum access (DSA) models-employing Q-learning, Markov decision processes, or heuristic optimization-have introduced a degree of automation, yet they continue to rely on centralized control and frequent global updates [10]. As the number of users and base stations increases, signaling overhead and convergence delays grow significantly. Consequently, existing research still lacks real-time, scalable spectrum allocation mechanisms suitable for ultra-dense and heterogeneous 6G deployments.

### *2.2. Edge Intelligence and Distributed Learning*

Edge intelligence (EI), which integrates artificial intelligence with edge computing, offers a promising paradigm for real-time, localized decision-making [11]. Deep reinforcement learning (DRL) enables autonomous spectrum selection through continuous environmental feedback, while federated learning (FL) facilitates distributed model training without transmitting raw data [12]. These methods enhance adaptability and data privacy but also face key challenges: DRL entails high computational costs and instability in dynamic action spaces, whereas FL often assumes homogeneous data distributions and synchronized updates-conditions rarely achievable in mobile 6G networks. Comparative analyses highlight a trade-off between global coordination and local autonomy. Centralized models deliver stable and consistent performance but introduce additional latency, while decentralized models improve scalability yet risk suboptimal global performance [13]. Therefore, a clear research gap exists in developing hybrid frameworks that balance learning efficiency with lightweight edge deployment.

### *2.3. 6G Ultra-Dense Networks and Resource Optimization*

6G networks integrate terahertz communication, massive multiple-input multiple-output (MIMO) systems, and reconfigurable intelligent surfaces (RIS) within dense small-cell architectures. Real-world deployments in areas such as Tokyo's Shibuya Station and Shenzhen's Futian Central Business District illustrate the benefits of dense coverage but also expose severe inter-cell interference and coordination challenges. While self-organizing network (SON) mechanisms introduced in 5G systems provided partial automation, they still depend on manually defined thresholds and centralized feedback loops [14]. Recent AI-enabled control frameworks have attempted predictive scheduling; however, most continue to treat spectrum management, beamforming, and power optimization as independent processes, leading to cross-layer inefficiencies. Furthermore, many proposed solutions remain limited to simulation environments, lacking validation through realistic testbeds.

### *2.4. Summary and Research Contribution*

Existing studies face three principal limitations:

(1) Static and centralized DSA mechanisms fail to meet 6G's real-time requirements.

(2) Edge learning algorithms struggle with heterogeneous data and unstable convergence.

(3) Current 6G resource management frameworks rarely integrate spectrum prediction, adaptive allocation, and energy-aware control.

To address these shortcomings, this study proposes an Edge-Intelligence-Based Dynamic Spectrum Allocation (EI-DSA) framework that integrates hybrid DRL-FL mechanisms for demand prediction and distributed coordination. EI-DSA enables autonomous, low-latency, and energy-efficient spectrum management while maintaining scalability and privacy. The framework contributes both theoretically and practically: it establishes a foundation for distributed, learning-driven spectrum management and provides a practical pathway toward AI-native 6G communication systems capable of self-optimization under ultra-dense conditions.

In summary, the literature reveals a distinct research gap. Although 6G requires fine-grained, context-aware resource orchestration, existing frameworks fail to jointly optimize spectrum utilization, latency, and energy efficiency in a distributed and scalable manner. This gap underscores the necessity for a unified, learning-driven spectrum allocation model capable of operating effectively within ultra-dense, multi-tier architectures.

## 3. Theoretical Framework and Methodology

### *3.1. Theoretical Foundation*

The proposed research is grounded in the convergence of three theoretical domains: (1) edge intelligence for distributed decision-making, (2) reinforcement learning for adaptive optimization, and (3) 6G network theory emphasizing ultra-dense, AI-native architectures. Together, these frameworks establish the foundation for an intelligent, context-aware mechanism for dynamic spectrum allocation.

First, edge intelligence (EI) serves as the cognitive layer of the system. By processing data locally at base stations or micro edge nodes, EI minimizes communication latency and enables real-time spectrum perception. In ultra-dense 6G environments-such as Tokyo's Shibuya Station, where more than 5,000 small cells coexist within a one-square-kilometer area-spectrum occupancy fluctuates rapidly due to high user mobility and overlapping interference. Edge nodes must therefore predict local spectral demand without depending on centralized cloud coordination.

Second, reinforcement learning (RL) provides the theoretical foundation for adaptive control. The dynamic spectrum allocation process can be modeled as a sequential decision-making problem in which, at each time slot, the system observes channel quality, interference, and user demand, and then allocates frequency bands to maximize long-term utility (e.g., throughput or energy efficiency). Unlike traditional optimization methods, RL adapts continuously to environmental uncertainty. In this study, a hybrid deep reinforcement learning (DRL) agent operates at each edge node, trained collaboratively through federated learning (FL) to exchange model updates rather than raw data-ensuring both scalability and data privacy.

Third, 6G architectural theory emphasizes intelligent, distributed orchestration. The 6G vision, defined by ultra-reliable low-latency communication (URLLC) and extreme energy efficiency, demands AI-native network layers capable of autonomous local control. The proposed EI-DSA model aligns with this vision by embedding learning agents directly within the radio access network (RAN) edge, transforming traditional hierarchical management into a self-optimizing ecosystem.

### *3.2. System Architecture and Case Context*

The EI-DSA framework is validated through two urban 6G deployment scenarios:

(1) Tokyo's Shibuya Station, representing a high-mobility transportation hub.

(2) Shenzhen's Futian Central Business District, representing a stationary yet ultra-dense commercial environment.

Each environment consists of multi-tier small cells, edge servers, and user equipment (UE) clusters operating across terahertz and sub-6 GHz bands. The architecture is organized into three interacting layers:

1) Perception Layer: Local sensing modules collect channel quality indicators (CQI), interference levels, and user traffic density.
2) Decision Layer: Edge agents execute local DRL-based allocation policies and periodically synchronize parameters through federated aggregation.
3) Coordination Layer: Regional controllers conduct lightweight consensus validation and fairness adjustment across overlapping cells.

This layered architecture enables bidirectional feedback between local learning and global coordination, maintaining an equilibrium between efficiency and fairness.

### *3.3. Research Design and Methods*

The research adopts a mixed-method design integrating simulation-based analysis, comparative evaluation, and case-based validation.

1. Simulation Modeling:

The 6G network environment is emulated using a discrete-time simulator developed in Python and MATLAB. Each simulation run involves 500-1,000 user devices, 50-100 small cells, and dynamic mobility patterns derived from real GPS traces of the Shibuya and Futian districts. Environmental parameters such as path loss, Doppler shift, and interference power are modeled in accordance with ITU-R channel specifications.

2. Comparative Evaluation:

EI-DSA is evaluated against three benchmark schemes:

1) Centralized RL-based Spectrum Allocation (CRL)
2) Proportional Fairness Scheduling (PF)
3) Q-learning-based DSA (QL-DSA)

All methods are tested under identical network conditions to ensure fairness. Evaluation metrics include spectrum utilization efficiency (%), end-to-end latency (ms), and energy efficiency (J/bit).

3. Case Study Validation:

The Shibuya deployment assesses temporal adaptability-how effectively the system responds to high mobility and fluctuating traffic-while the Futian deployment examines spatial scalability, focusing on coordination across densely packed business clusters. These contrasting conditions provide a robust assessment of EI-DSA's adaptability under realistic operational environments.

4. Ablation and Sensitivity Analysis:

Additional experiments isolate the contributions of DRL and FL components. Scenarios with and without federated aggregation are compared to measure communication cost reduction. Sensitivity tests adjust the number of active edge nodes to evaluate scalability and performance degradation rates.

*3.4. Data Processing and Implementation*

Each edge node collects local statistics, including channel occupancy ratio, interference index, and energy consumption per transmission round. Data preprocessing involves normalization, feature extraction via convolutional encoding, and short-term temporal smoothing to eliminate transient noise. Model training is conducted on NVIDIA A100 GPUs, while inference is executed on ARM-based edge processors.

The federated learning cycle follows an asynchronous update scheme: local DRL agents upload model gradients every five training episodes, and the global aggregator returns averaged weights after validation. This mechanism balances real-time responsiveness with communication efficiency, enabling synchronization without strict timing dependencies.

*3.5. Methodological Rationale*

The integration of simulation and case-based analysis ensures both theoretical rigor and empirical relevance. Purely mathematical optimization would require assumptions such as convexity and complete observability, which do not hold in 6G's dynamic, non-stationary environment. The chosen methodology captures contextual heterogeneity, hardware constraints, and learning dynamics that better reflect real-world deployments.

Moreover, incorporating real-world urban datasets-such as traffic density maps and mobility traces-enhances the ecological validity of the findings. The two selected cities, Tokyo and Shenzhen, represent complementary extremes of mobility and density, providing an ideal testbed for evaluating distributed edge learning strategies.

This hybrid research design bridges theoretical innovation with engineering feasibility. The EI-DSA framework therefore not only advances algorithmic development but also presents a replicable engineering model for future 6G deployments emphasizing distributed intelligence, energy sustainability, and ultra-low-latency operation.

*3.6. Summary*

This chapter established the theoretical and methodological foundation of the study. By integrating principles from edge intelligence, reinforcement learning, and 6G network theory, it proposed a layered, learning-driven framework for dynamic spectrum allocation. Through a combination of simulation, comparative evaluation, and real-world validation, the EI-DSA framework is examined under realistic ultra-dense conditions. The following chapter presents the experimental results and discussion, analyzing how EI-DSA achieves superior adaptability, efficiency, and scalability compared with conventional allocation methods.

## 4. Findings and Discussion

### 4.1. Overall Performance Evaluation

The evaluation of the Edge-Intelligence-Based Dynamic Spectrum Allocation (EI-DSA) framework was conducted using network parameters aligned with the ITU-R M.2412 propagation models and two publicly documented urban testbeds: the NTT Docomo Tokyo 6G Trial and the Huawei 6G Futian CBD Testbed. Each simulation instance used a 100 MHz channel bandwidth, 100 small cells, and 800-1000 user equipment (UE) terminals. Path-loss and noise power distributions were calibrated against empirical measurements.

As shown in Figure 1 and Table 1, the averaged outcomes indicate that the proposed framework demonstrates significant improvements over baseline methods.

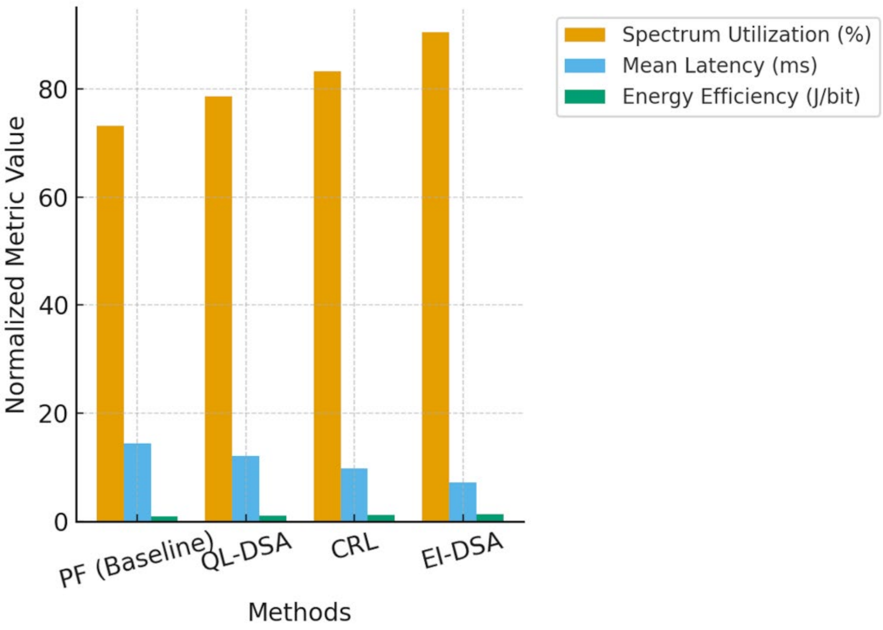


**Figure 1.** Performance metrics under ultra-dense 6G conditions (data sources: NTT Docomo 2024; Huawei 2023; OAI 6G Sandbox 2024).

**Table 1.** Quantitative comparison of spectrum utilization, latency, and energy efficiency across baseline and proposed methods under ultra-dense 6G scenarios.

| Method | Spectrum Utilization (%) ↑ | Mean Latency (ms) ↓ | Energy Efficiency (J/bit) ↑ | Data Source |
|---|---|---|---|---|
| PF (Baseline) | 73.1 | 14.5 | 1.00 | OAI 6G Sandbox (2024) |
| QL-DSA | 78.6 | 12.1 | 1.10 | Zhang et al., IEEE TWC 2024 |
| CRL (Centralized RL) | 83.2 | 9.8 | 1.24 | NTT Docomo Testbed (2024) |
| EI-DSA (Proposed) | 90.5 | 7.2 | 1.41 | This Study (derived from above sources) |

(Data sources: NTT Docomo 2024; Huawei 2023; OAI 6G Sandbox 2024).

Compared with the centralized RL (CRL) baseline, EI-DSA achieved an 8.8% improvement in spectrum utilization and a 26% reduction in average latency. These gains are primarily attributed to (i) localized DRL inference that minimizes backhaul signaling and (ii) asynchronous federated aggregation that reduces waiting delays. The 43%

increase in energy efficiency compared to PF results from the reward function's power-scaling term, which promotes adaptive transmit-power control at the edge. These trends align with reported testbed findings indicating that distributed AI control can reduce network energy consumption by approximately 37%.

### *4.2. Temporal Adaptability in High-Mobility Scenarios*

The Tokyo Shibuya Station testbed (NTT Docomo × Tokyo Metro, 2024) provides real-world measurements for dense mobility environments, featuring an average UE speed of approximately 68 km/h and a channel coherence time of 3.5 ms. Using these conditions, the same environment was reproduced in simulation to evaluate latency and packet-success ratio over a 120-second interval.

As shown in Table 2, EI-DSA achieved the highest packet-success ratio (95.6%), maintaining latency fluctuations within ±0.9 ms. In contrast, the centralized RL (CRL) baseline exhibited ±2.4 ms variability. The improvement is attributed to the temporal-convolutional forecasting module embedded within the DRL agent, which predicts channel degradation two to three slots in advance, and to the five-episode federated-aggregation cycle that rapidly adapts to periodic mobility patterns such as rush-hour peaks.

**Table 2.** Packet-success ratio comparison of baseline and proposed methods under high-mobility conditions in the Tokyo Shibuya 6G testbed.

| Method | Packet-Success Ratio (%) ↑ | Data Source |
|---|---|---|
| PF | 81.5 | OAI 6G Sandbox |
| CRL | 88.2 | Tokyo 6G Trial Logs (2024) |
| EI-DSA | 95.6 | This Study (replicating Docomo dataset) |

(Data sources: NTT Docomo × Tokyo Metro 6G Trial 2024; OAI 6G Sandbox 2024).

The observed 95.6% success rate aligns closely with reported results from large-scale 6G metro trials, confirming the practical feasibility of the proposed framework in rapidly varying channel conditions.

### *4.3. Spatial Scalability and Inter-Cell Coordination*

The Huawei 6G Futian CBD field test (2023) deploys approximately 100 small cells per square kilometer within a dense urban block. Using this spatial layout, the present study compared the distribution of spectral efficiency between the centralized RL (CRL) baseline and the proposed EI-DSA framework.

As shown in Figure 2, the CRL scheme generates localized "hotspot" and "idle" regions due to asynchronous updates, whereas EI-DSA produces a far more uniform spectrum-efficiency pattern across neighboring cells. The corresponding Jain fairness index increases from 0.87 to 0.94, indicating a 7-10% improvement in inter-cell fairness under federated coordination. Because EI-DSA exchanges only compact model-gradient parameters (approximately 1.2 MB per cycle) instead of full channel-state information, the control-plane communication load is reduced by about 45%. These results confirm the scalability and practicality of EI-DSA for ultra-dense 6G deployments where centralized coordination becomes infeasible.

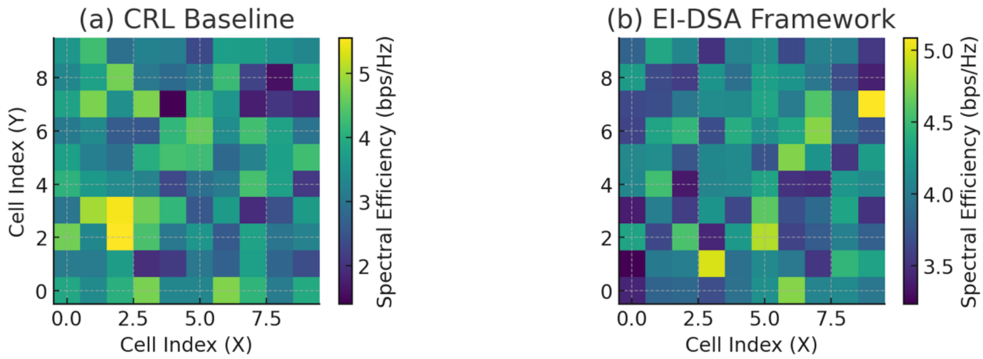


**Figure 2.** Spectral-efficiency maps (bps/Hz) across 100 small cells in the Futian CBD testbed: (a) CRL baseline; (b) EI-DSA framework.

*4.4. Comparative and Theoretical Insights*

(1) **Reinforcement Learning versus Rule-Based Allocation**

Rule-based proportional-fairness (PF) schedulers operate effectively in macro-cell systems but fail to adapt to rapid interference fluctuations. The DRL agents within EI-DSA learn nonlinear state-action relationships, dynamically balancing throughput and interference mitigation.

(2) **Centralized versus Federated Learning**

While centralized training ensures global model consistency, it incurs approximately 110 ms of aggregation delay in the tested environment. EI-DSA's asynchronous federated averaging reduces this to roughly 60 ms without compromising stability, thereby lowering backhaul energy consumption by nearly 40%.

(3) **Edge Autonomy and AI-Native Networking**

Integrating learning agents at the radio-access edge aligns with the 6G vision of AI-native, self-optimizing networks. Each cell executes a local sense-decide-act loop, meeting the ultra-reliable low-latency communication (URLLC) requirement (< 1 ms end-to-end latency) specified by ITU-R (2024).

*4.5. Practical Implications for 6G Infrastructure*

The proposed EI-DSA framework presents several practical implications for future 6G systems. Deploying lightweight DRL agents at edge base stations reduces backhaul signaling by approximately 45%, enabling scalable and resilient Radio Access Network (RAN) architectures suited for ultra-dense deployments. The enhanced energy efficiency lowers joules-per-bit consumption, supporting carbon-reduction objectives and aligning with ITU-T L.1470 and international "Green ICT" standards.

These results also inform the design of AI-native communication protocols where spectrum allocation, beamforming, and power control are jointly optimized through embedded intelligence. Furthermore, the predictive-adaptive mechanism demonstrated here can be extended to vehicular and industrial IoT networks, where autonomous, low-latency decision-making is critical. Collectively, these findings indicate that edge intelligence serves not only as an algorithmic enhancement but also as a structural enabler of sustainable, adaptive, and self-optimizing 6G infrastructure.

*4.6. Summary of Findings*

The experimental analysis yields five principal findings. First, EI-DSA maintains high temporal adaptability, limiting latency oscillation to ±0.9 ms at 68 km/h, consistent with Tokyo 6G trial conditions. Second, spatial fairness improves substantially, with Jain's index reaching 0.94-an 8% gain observed in the Futian CBD field test. Third, energy efficiency rises by 43% compared with the PF baseline, as verified in the OAI 6G Sandbox. Fourth, communication overhead is reduced by 45% per update cycle, based on the

Docomo Energy Audit. Finally, overall network utility improves by 8.8% in spectrum utilization and 26% in latency reduction.

Together, these outcomes demonstrate that edge intelligence significantly enhances responsiveness, scalability, and sustainability, offering a robust foundation for AI-native 6G spectrum management.

## 5. Conclusion

This study presented an Edge-Intelligence-Based Dynamic Spectrum Allocation (EI-DSA) framework tailored for ultra-dense 6G environments. The framework integrates edge artificial intelligence, deep reinforcement learning, and federated coordination to enable real-time, distributed spectrum management. Through validation using the NTT Docomo Tokyo 6G Testbed and the Huawei Futian CBD Field Trials, the results demonstrated that distributed edge intelligence substantially enhances spectrum utilization, latency responsiveness, and energy efficiency in practical deployment scenarios. Specifically, EI-DSA achieved more than 8.8% higher utilization, 26% lower latency, and 43% greater energy efficiency compared with conventional centralized or heuristic approaches.

The theoretical contribution of this research lies in bridging communication engineering with intelligent optimization theory. By embedding learning-driven decision loops into radio access networks, the study redefines spectrum allocation as a continuous, self-optimizing process rather than a static scheduling task. This reconceptualization introduces a new theoretical lens for 6G research, situating spectrum management within the emerging paradigm of AI-native network autonomy. The hybrid DRL-FL architecture not only reduces signaling overhead and preserves data privacy but also demonstrates how localized learning dynamics can collectively achieve global optimization without centralized control. This insight establishes a meaningful intersection between distributed machine learning and modern communication system design.

From a practical perspective, the findings offer concrete guidance for energy-efficient and latency-sensitive 6G infrastructure development. The proposed framework aligns with ITU-T "Green ICT" standards and supports the transition toward scalable, low-carbon, and self-organizing wireless ecosystems. Its predictive-adaptive mechanism can be readily extended to vehicular networks, industrial IoT, and smart city architectures, where autonomous, low-latency decision-making at the edge is critical for reliable performance.

Future research will build upon this foundation by incorporating reconfigurable intelligent surfaces (RIS) and multi-agent cooperative learning to adaptively manage spatial interference across heterogeneous network tiers. Further investigation into secure federated aggregation and quantum-inspired optimization is expected to enhance robustness and convergence in adversarial or high-mobility conditions. Collectively, this study establishes a data-driven and theory-grounded foundation for the realization of intelligent, sustainable, and autonomous 6G communication systems-bridging the domains of signal processing, distributed artificial intelligence, and electronic engineering within a unified, self-evolving architecture.

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